Assessing and Attributing Climate Change Response of U.S. Insurance Firms

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Abstract

Climate change poses as a serious risk for insurance firms, threatening the affordability of the impact of insurance risks and sustainability of the firms. However, the impact of climate change risk and the propensity of insurance firms to respond to this risk is difficult to assess due to lack of consistent reporting frameworks. In this research, we apply textual analysis to 10-K regulatory filings of 122 insurance firms to assess and distinguish between the firms' response to climate change risk, and how their responses relate to their financial and governance characteristics using a multiplex network clustering analysis. Identification of this relationship will help advice the favorable factors that enhance the propensity of insurance firms to develop a climate risk strategy. Our results show that most of the insurance firms with high exposure to climate change risk present low level of adaptation. Analysis at the industry sector indicates that most casualty and surety insurance firms are threatened by high climate change risk, with a high exposure on chronic risk for surety firms. Furthermore, insurance firms with bad response for high climate change risk exposure tend to have fair financial performance ratios with a high connection in governance characteristics at the board level.

Keywords: Climate Change, Insurance Firms, Textual Analysis, Multiplex Network Analysis

JEL Codes: D85, G22, G32, Q54

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1 Introduction

Climate change has repeatedly threatened the short-term liquidity of U.S. insurance firms and poses a potential challenge on the industry's sustainability in the long run (Mills, 2005). The high frequency of disasters caused by climate change has led to irreparable economic loss amounting to $50 billion per year (Mills, 2012), resulting in large accumulated deficits for insurance firms (Milly et al., 2002; Field et al., 2012; Changnon, 2003). Given the important role of the insurance industry in global financial health, climate change risk should be seriously recognized as an insurance risk and tackled by all insurance firms to ensure the sustainability of the industry and the global financial market. Investors and the public want to know how companies mitigate and adapt to the impact of climate-related risks. However, a systematic assessment of how the insurance industry, at an individual firm level, is responding to climate change risks can be challenging since there are no consistent or standard reporting frameworks for firms to disclose their exposure to climate change risk.[1]

Given that most of the firms' climate change risk information are disclosed in the form of text, we propose in this paper, the use of textual analysis of U.S. insurance firms' 10-K regulatory files to extract and define features, to assess and distinguish between firms' response to climate change risk. We analyze the variations across insurance firms in their climate change responses and use a multiplex network clustering analysis to seek insights on how the textually defined climate change response features relate to the insurance firms' financial and governance characteristics. Assessment of this relationship can help identify the channels of influence for climate change response and climate risk preparedness among insurance firms.

To examine the responses of insurance firms to the risks posed by climate change, past researchers have evaluated various strategies of insurance firms. These strategies can be grouped into traditional and innovative methods. Traditional methods focus on avoiding and mitigating climate risk in the short-term. Avoidance strategies are utilized to withdraw from high climate risk related markets to reduce the possibility of potential disaster-related insured losses (Thomas and Leichenko, 2011). Mitigation response strategies focus on actions that mitigate climate risk losses both before and after severe disasters. Insurance firms raise the premium rate for climate sensitive corporations (Maynard, 2008), limit the coverage proportion (Elum and Simonyan, 2016) as well as rely on partially shifting insurable responsibility on to the government to lower their actual insurance liability (Groth and Muntermann, 2011).

Innovative methods include adapting to climate risk by investing more on climate analysis and prediction techniques (Hecht, 2007). Insurance firms continue to evaluate climate change signals by analyzing historical data to prepare for potentially elevated insurance claims. More effort is devoted to collaboratively analyze and collect climate-related catastrophe data as well as increasing investment on authoritative climate research institutions, such as United Nations Environmental Program (UNEP) and The National Flood Insurance Program (NFIP) (Keskitalo et al., 2014), to

[1] Final Report: Recommendations of the Task Force on Climate-related Financial Disclosures (June 2017). https://www.fsb-tcfd.org/publications/final-recommendations-report/

predict climate risk impact. Multiple insurance firms have built their own weather-risk models (Pollard et al., 2008) according to climate, geography, society and insurance environment factors to foresee the impact of climate change. Similarly, catastrophe models have been adapted to help insurers predict and assess the property damage under different scenarios in multiple regions (Mills, 2003; Kousky and Cooke, 2009).

As most climate change responses of insurance firms are documented as texts, which is unstructured data, a combination of textual analysis and machine learning methods would prove to be effective in assessing firms' responses. Past research has studied the relationship between textual information and other market or firm signals by implementing sentiment analysis and machine learning methods on textual content of news articles (Creamer et al., 2016), regulatory filings (Li, 2010; Gupta and Owusu, 2019), reports (Ntim et al., 2013), blogs and emails released by firms (Shivdasani and Yermack, 1999; Fecamp et al., 2019). In our study, we extract textually defined features to identify climate change responses of U.S. insurance firms using 10-K regulatory filings available in the U.S. Securities and Exchange Commission (SEC) EDGAR System. 10-K filings are one of the most comprehensive and consistent documents available for publicly listed firms. The filings provide information on the firms' financial health and also contain risk sections (Item 1A and 7) with discussions on the risks the firm faces. Thus, making them ideal for our study on climate change risk.

We build a climate change dictionary as a reference source for our textual analysis and feature extraction. Our dictionary is made up of 3 sub-dictionaries capturing the climate change risk, impact and response of the firm. The climate change risk sub-dictionary defines the acute and chronic risks the firm faces whiles the climate change impact sub-dictionary captures the pecuniary and non-pecuniary impacts and losses posed by the climate risks faced. The climate change risk response sub-dictionary focuses on the traditional, innovative and governance strategies to adapt, mitigate and transfer climate change risk. From the climate risk sub-dictionaries and categories, we create keywords and phrases, and implement a nested structure extraction to enhance our extraction accuracy. We define our textually defined features for the climate change response of the insurance firms by counting the occurrence of the keywords in each firm's 10-K report.

After extracting the climate change features, we follow a semi-manual 'hierarchical' clustering approach to precisely characterize the different level of risk exposure with different levels of adaptations to assess firms' climate change responses. Consequently, we use a two-step classification to group insurance firms according to their climate change risk exposure and adaptation level. A multiplex network clustering analysis process is conducted to attribute firms' climate change responses to the firms' financial performance and governance characteristics. Stechemesser et al. (2015) relates the firms' adaptation level of climate change to firm performance and find a positive correlation between climate change adaptation response and return on asset (ROA). Also the insurance industry's response to risks has been proven to be significantly shaped by the firms' governance (Tornyeva and Wereko, 2012). The risk disclosure for firms is positively influenced by their size, diversity and the number of independent non-executive directors on the corporate board

(Ntim et al., 2013).

The assessment of climate change response shows that only 20% of insurance firms actively respond to climate change. Results of firms' climate characteristic show that firms with high exposure to climate risk present low level of adaptation. Analysis at the industry sector indicates that most casualty insurance firms are exposed to high climate change but show a passive adaptation to climate change risk. Similarly, surety insurance firms present a low response level to high chronic risk they faced. Oppositely, life insurers adapt the chronic risk in a high level. Results of the multiplex network clustering analysis shows that firms with bad response level to a high climate risk exposure have connections at the governance level and fair financial performance ratios, while firms with better adaptation response to climate change risk show less connections in governance and financial characteristics. We also find casualty, surety and life insurance firms to have active connections at the governance level.

Our paper contributes to existing literature on how to assess insurance firms' climate change response. First, we contribute a climate change dictionary and vocabulary of keywords to textually identify climate change risk, impact and response. Our textual analysis approach and two-step classification enable us to group firms based on their response to their climate change risk exposure and their adaptative level. Second, we systematically attribute firms' climate change response to their financial and governance characteristics. The multiplex layer network clustering analysis approach effectively relate firms' climate change response clusters to their financial and governance characteristics to finally provide insights for the favorable factors that can enhance insurance firms' propensity to develop a climate risk strategy.

The rest of paper is organized as follows. Section 2 introduces the climate change dictionary and our approach to extract climate change features and attribute climate change risk response to financial and governance characteristics of the firm. Section 3 describes the sample of firms, textual data, financial and governance data used in our study. We summarize our findings in Section 4, and conclude and discuss future direction of our study in Section 5

2 Methodology

This section discusses the construction and analysis approach used in our study to attribute firms' climate change responses to their financial and governance characteristics. We introduce our climate change dictionary and the approach used to extract climate change features from text documents. Our main analysis to assess the firm characteristics is explained in Sections 2.3 and 2.4.

2.1 Building Climate Change Dictionary

To identify climate change features from textual data, we need to build a climate change dictionary to guide our feature extraction process. Since the assessment and attribution of climate change for insurance firms should be captured and evaluated from the risk and uncertainty posed by climate change, as well as the impact and response of the firm to climate change, we begin by creating 3 sub-dictionaries. The sub-dictionaries are 'Climate Change Risk Dictionary,' 'Climate Change Impact Dictionary' and 'Climate Change Response Dictionary'. Figure 1 displays the sub-dictionaries within the climate change dictionary and their categories.

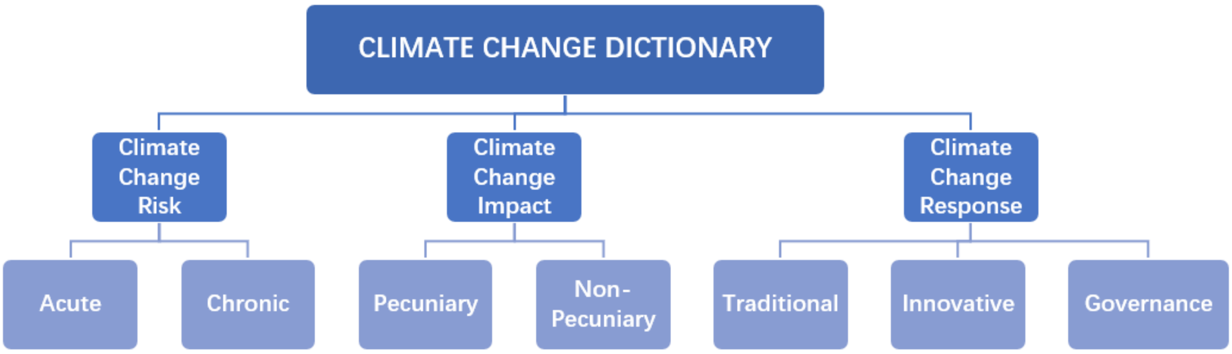


Figure 1: Climate Change Dictionary

In the first sub-dictionary 'Climate Change Risk Dictionary', two categories *Acute* and *Chronic* are set to classify the risks from climate change based on the TCFD Final Report (Bloomberg et al., 2017). Acute risk represents events that are driven by climate change, including extreme catastrophes and severe weather events such as typhoon, hurricane and tsunami. Chronic risk refers to long-term pattern shifting of climate change such as ocean acidification, soil deterioration and sea-level rise.

For the 'Climate Change Impact Dictionary', *Pecuniary* and *Non-Pecuniary* are the two categories used to capture the impact posed by climate change to the insurance industry. Pecuniary category describe financial losses such as insured loss, cumulative debt and unaccountable losses which threatens the sustainability and liquidity of insurance industry and the financial market. The Non-Pecuniary category describes the non-financial loss posed on the society which will potentially do harm to the development and operation of the society. Examples include climate-related disruption, Lyme disease and refugees.

The last sub-dictionary, 'Climate Change Response Dictionary' is classified by *Traditional*, *Innovative*, and *Governance* categories to capture the response made by insurance firms and government to adapt, mitigate and transfer climate change risk. The Traditional category describes the firms' traditional approach to mitigate and avoid climate change risk in the short-term such as increasing premium, coverage limitation or withdrawing from climate risk related markets. The Innovative category represents the firms' active adaptation for climate change in the long run. This may include the use of green bonds or climate bonds, reinsurance, and investing in renewable energy. The Governance category represents the research, financial and policy support from the government to tackle climate change risk. Initiatives such as pay-as-you-drive, public-private patchwork and Carbon Disclosure Project (CDP) are included in this category.

To build the vocabulary of words for our climate risk dictionary, we sample 33 climate change white papers over the period 1997 and 2019 from the Intergovernmental Panel on Climate Change (IPCC), the U.S. EPA, International Monetary Fund (IMF), U.S. Global Change Research Program, Task Force on Climate-Related Financial Disclosures (TCFD), United Nations Environmental Programme (UNEP) and Network for Green the Financial System (NGFS). We further enlarge our climate change repository to construct an exclusive and scientific climate change dictionary, using the 24 climate change glossaries proposed by Engle III et al. (2019) for additional climate change knowledge supporting sources. The 24 climate change glossaries are summarized in Table A1 in the Appendix.

2.2 Nested Structure Feature Extraction

Given our climate change dictionary consists of words or phrases under the categories of each sub-dictionary, a direct count of the occurrence of words and phrases in the dictionary for feature extraction will not be reliable. Words in each phrase may not always appear in the same order or distribution in the text document. For instance, the phrase 'weather-related disaster', may be stated as 'weather and natural disasters', or 'weather-related or other natural or man-made catastrophes and disasters'. Thus a traditional bag of words extraction of features will make it almost impossible for us to build a comprehensive dictionary, making our extraction process less accurate.

Considering the complexity of natural language processing and the flexibility of phrases used in the text documents, we create a nested structure of our taxonomy to ensure a robust and sound searching criteria to capture the occurrence of phrases.

The nested structure is constructed under the category level of each sub-dictionary which gives us 7 nested "trees" (Acute, Chronic, Pecuniary, Non-Pecuniary, Traditional, Innovative, Governance) as reference for extraction. For each tree, the node of the first level is set as the word that represents the core meaning of each phrase or word. For instance, in the phrase *'sea level rise'*, we select *'sea'* as the first level node of this phrase. Then we expand the branch and level of our tree by appending the parent node's related words that are present in the same phrase. The order of placing the words in each level of node is determined by the importance and relevance of each word in the phrase. Figure 2 shows an example of a nested structure of an Acute tree from the 'Climate Change Risk Dictionary' sub-dictionary. All words within the phrases are stemmed to their root or base word.

To extract the climate change features, we form a hierarchical extraction at the sentence level. Our extraction can be mainly separated into two parts, a *Climate Change Risk* extraction and a *Climate Change Impact & Response* extraction. For our Climate Change Risk extraction, we count the occurrence of each word based on the level in the hierarchy. Words at lower level of the hierarchy are only counted if their parent node is present in the same sentence. Multiple occurrences of the same word in a sentence is only counted once. The first level nodes in the count tree is summed up and set as the value of climate change risk Acute and Chronic features. The same counting procedure is applied to the Climate Change Impact and Response dictionary

Figure 2: Example of the Nested Structure using the Acute Dictionary Tree

trees. In order to assess the impacts and responses in the context of only climate change risks, the search is limited to sentences where climate change risk keywords are present. In all, we identify 8 features to assess firms' recognition of climate change. These are 'Acute Risk', 'Chronic Risk', 'Acute Pecuniary', 'Chronic Pecuniary', 'Acute Non-Pecuniary', 'Chronic Non-Pecuniary', 'Acute Response' and 'Chronic Response'.

Referring to Figure 2 as an example, for each sentence of the text document, we start by finding whether there is any occurrence of the word *'rain'*. If there is an occurrence of *'rain'* in that specific sentence, the node in the count tree will be counted as 1. Moving further, if the node in the count tree, that is, in the comparable position of *'rain'* in the original tree is not 0, then we search and record whether there is any occurrence for the word *'fall'* which is the second level node related to *'rain'*. When done searching through all of the branches for *'rain'*, we move to the next first-level node 'atmospher'. After counting all of the nodes of the acute risk tree, we apply the process on all of the sentences in the text document. Finally, we sum up the values on the nodes that belong to the first level of the tree as the value of Acute risk features of the text document.

2.3 Assessing Firm Characteristics

Once we have extracted the climate risk features from our text document, we assess how firms are responding to climate change risk by classifying them according to their exposure to climate change risk and adaptative level. We also compare the climate risk response of the firms to their financial and governance characteristics using key financial indicators such as liquidity, profitability, leverage, size, insurance industry specific operational loss ratio and board networks.

2.3.1 Climate Change Characteristics

We apply a two-step approach to classify firms based on their climate change risk characteristics. In the first step, a splitting process to characterize firms' climate change risk exposure is conducted on the sample of firms using 68% confidence interval [2] of the logarithm of the number of occurrence

[2] 68% confidence interval: $(\mu \pm \sigma)$

for climate change risk. This split setting forms a *general* classification of firms' climate change risk characteristics. Four segments are created: 'High Acute & High Chronic Risk (HAHC)', 'High Acute & Low Chronic Risk (HALC)', 'Low Acute & High Chronic Risk (LAHC)' and 'Low Acute & Low Chronic Risk (LALC)'. The preliminary classification can be observed in Figure 3 below.

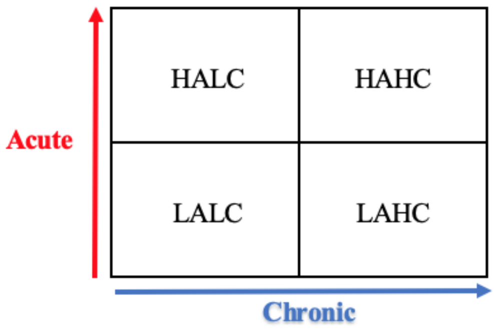


Figure 3: General Classification of Firms based on Climate Change Risk

Firms in each segment are expected to have different climate change characteristics. In the second step, a *further* classification of firms based on the level of impact and response pertaining to the climate change is applied to further split the four groups created in the first step. For instance, firms in the HAHC group are examined for both acute- and chronic-based impact and response. While, HALC and LAHC groups are examined for only their acute impact and response or chronic impact and response respectively. Since firms in the LALC group do not have significant focus on climate change risk features, the group is not pursued for further classification.

Firms which have related higher impact but lower response are determined as *'Bad'* related risk adaptation group. While lower impact but with higher response were assigned to the *'Good'* related risk adaptation group. By conducting the method above, firms were continuously split further into either four or two groups for each segment in Figure 3 except for LALC. For instance, HAHC firms are separated into 'Good Acute & Good Chronic' Risk Adaptation (GAGC), 'Bad Acute & Good Chronic' Risk Adaptation (BAGC), 'Good Acute & Bad Chronic' Risk Adaptation (GABC) and 'Bad Acute & Bad Chronic' Risk Adaptation (BABC). HALC group are separated into 'Good Acute' Risk Adaptation (GA) and 'Bad Acute' Risk Adaptation (BA). LAHC firms are split into 'Good Chronic' Risk Adaptation (GC) and 'Bad Chronic' Risk Adaptation (BC). By this two-step approach, we classify our firms based on their climate change textual features.

2.3.2 Financial Characteristics

An unsupervised cluster analysis method is used to classify firms according to their financial features. We apply K-means clustering technique to partition the firms in our sample to K-groups (MacQueen et al., 1967). Each firm is assigned into one of the K groups according to the distance the observation is from the mean centroid of each cluster.

The first step in our cluster analysis is to determine the number of clusters (K) to be formed.

We use the Silhouette Analysis (Rousseeuw, 1987) to measure the tightness or how close each point in one cluster is to points in the neighboring clusters. A silhouette coefficient near +1 means the sample point is far away from the neighboring cluster while a coefficient near -1 shows that the sample point must have been assigned to the wrong clusters. A silhouette coefficient of 0 means the sample point is on the boundary between two neighboring clusters.

$$\text{Silhouette Coefficient} = \frac{b - a}{max(a, b)} \tag{1}$$

where a is the intra-cluster mean distance and b is nearest cluster distance.

We also apply a feature selection approach to determine the important features to add in our silhouette analysis. Features with high normalized standard deviation and low correlation with other features are first added in the silhouette analysis. Thus, the number of clusters to form is determined based on a combination of the silhouette coefficient and selection of features.

2.3.3 Governance Characteristics

To explore firms' governance characteristic, we build a firm network using the connections between board members and top executives. A matrix was created to present firms' connection by recording the number and names of common board members and top executives to let us get a basic idea of their networks. To make the connection more visual, we form a weighted network analysis graph. Each individual firm is set as a vertex and the weighted edges between each vertex is considered as common board members and top executives between the two firms. The shorter the edges are, the more common board members and top executives between the two firms. Through this process, a clear and precise network that presents the 'cluster' of insurance firms at the governance level is created.

2.4 Multiplex Layer Network Clustering Analysis

In order to attribute the climate change characteristics of insurance firms to the financial and governance characteristics, a multiplex network clustering analysis approach is applied. We form a 3-layer structure, where the three layers are according to firms grouping of climate change risk features, groups from the connections between board members and top executives and clustering of financial variables. The three layers are shown in Figure 4. Each layer creates a network of individual firms which we refer to as groups or clusters in that layer.

The first layer represents clusters of firms based on the climate change textual characteristics. The second layer describes the governance characteristics of firms formed by the network of common board members and top executives and the third layer shows clusters defined by the financial characteristics. After constructing the three layers, we analyze the relationship between the layers from the networks formed in each layer. By grouping firms according to climate change characteristics, we examine the financial and governance characteristics of firms in each climate change group. A sequential clustering identification method is implemented by hierarchically finding the

Figure 4: Three-Layer Structure for Graph Clustering

connections between firms according to the three characteristics. For instance, we start with the cluster of firms in the first layers and find out whether they are connected with cluster of firms in the second layer by assessing connections in governance or board networks. Once we identify a link, we proceed to connect this link with the third layer by financial characteristics.

Furthermore, we add firms' industrial sectors for the final sequence analysis for multiplex network since climate change exposure levels for different sectors will vary. For example, firms in casualty industry may suffer more impact from climate change, especially from acute climate risk compared to firms in life and accident and health (acchealth) industrial sectors. While firms in acchealth and life industry may be exposed to much climate change risk than firms in the surety and title sectors. Consequently, a 4-dimension multiplex network is formed for further analysis.

3 Data

In this section, we introduce the textual data source for climate change assessment, define our sample of firms and describe the firm characteristic variables used in our analysis. Definitions as well as the summary statistics of the financial and governance data variables are also discussed.

3.1 Textual Data

For our source of text data, we use 10-K regulatory filings available in the SEC EDGAR system. The 10-K is filed annually by publicly traded firms and provides comprehensive information about the business, financial condition, operations and risks of the firm. The risk sections in the 10-K files, Item 1A and Item 7, include discussions on the types of risks and impacts on the firms' operations. For insurance firms, especially for firms in casualty category, which contains over half of our observations, usually objectively set at least acute risk such as earthquake, windstorm and hurricane as default risk to their companies.

Each firm is assigned a unique Central Index Key (CIK) number when they file a report with SEC. We rely on the CIK number to assess the 10-K filings from the EDGAR database. Before extracting features from a text data or document, the raw unstructured text files must first be converted into a clean, recognizable and uniform text corpus. In pre-processing our text data, non-informative objects such as html tags, figures, charts and tables are removed from the file to obtain a readable format of the text document. To further enhance the document for feature extraction, we also remove stop words such as 'a', 'the', 'of', 'that' and other non-formative conveying common English language words. The remaining words in 10-K files are stemmed and converted into lowercase. Stemming words ensures that all potential words with the same meaning are captured. For instance, a word such as 'increase' can occur as 'increasing', 'increases' or 'increased' within the same document. Without stemming the main word as well as the other words, we miss capturing the complete occurrence of the word.

3.2 Sample of Insurance Firms

To identify our sample of insurance firms, we select firms with Standard Industrial Code (SIC) between 6311 and 6411 from the Compustat database. To ensure that each firm matches with a 10-K filing from the SEC EDGAR database, we require the firm to have non-missing CIK number in Compustat. We identify 315 insurance firms and download a total of 3,015 10-K reports from the earliest year available in the EDGAR database, 1984 to 2018. Going by the SIC code, there are eight industrial sectors within the insurance industry, namely, 'Accident and Health (Acchealth),' 'Agents,' 'Carriers,' 'Casualty,' 'Hospital and Medical (Hosmed),' 'Life,' 'Surety' and 'Title'. Figure 5 shows a distribution of the filings over time by industry sector. We find on average a large number of filings by casualty firms and the least by carriers.

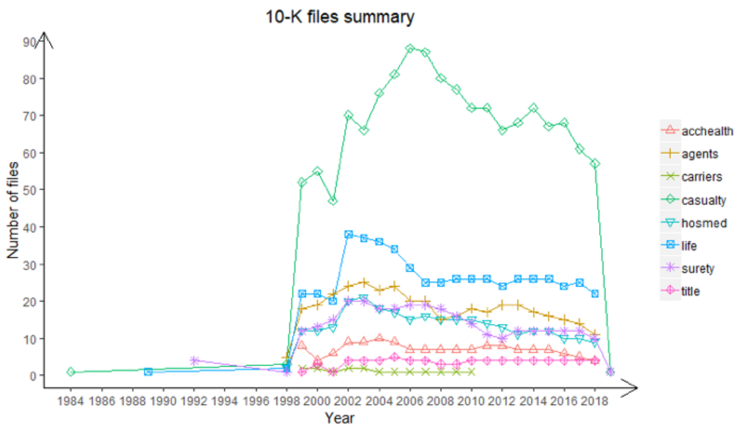


Figure 5: The Number of 10-K Regulatory Files By industry Group and Year

To ensure we have a rich content on climate change discussion in the 10-K filings, we narrow down and focus on a time period when climate change awareness was high enough to impact the firms' reporting in their filing. The Engle III et al. (2019) Wall Street Journal Climate Change News Index shows an average increase in the number of climate change news in the U.s. after the 3rd National Climate Assessment and the Environmental Protection Agency (EPA) Climate Change

Initiative in mid-2014. According to an analysis by National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS), 2014 was the warmest year in modern records among past years [3]. Thus, we set our research period from 2014 to 2018 fiscal year which reduces our final sample to 132 insurance firms with 630 10-K reports filings.

3.2.1 Outlier Detection

Following our discussion in Section 2.3.1, we filter out firms with extremely low occurrence of climate change risk words or phrases. Using the mean minus the standard deviation of the logarithm of the number of occurrence of climate change acute and chronic risk words, our sample of 132 firms is split into four groups as shown in Figure 6.

In the lower left segment of Figure 6, we observe a sample of 10 firms with extremely low recognition of acute and chronic risks (LALC). We drop these firms from our sample and obtain a sample of 122 firms. The lower right segment contains firms with high acute low chronic (HALC) words. The upper left and right segments are made up of firms with low acute high chronic (LAHC) and high acute high chronic (HAHC) words respectively. From our sample of 122 firms, we observe a total of 8, 10 and 104 firms in the HALC, LAHC, HAHC respectively.

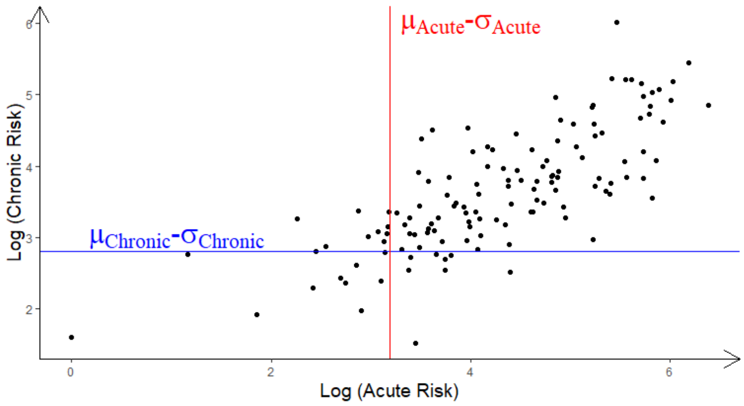


Figure 6: Outlier Firms Searching Graph

3.3 Financial and Governance Features

We obtain firm financial and governance data from the S&P Capital IQ database. The *Financial/Valuation* category provides firm financial data and includes key statistics from the income statement, balance sheet, cash flow statement, capitalization, capital structure and financial ratios for evaluating the sustainability and profitability of our sample of insurance firms. We obtain data to estimate the size of the firm, Return On Asset (ROA), leverage, quick ratio and expense ratio. Firm size is defined as the logarithm of total assets.

[3]https://earthobservatory.nasa.gov/images/85083/2014-was-the-warmest-year-in-the-modern-record

ROA measures the firms' profitability and is calculated by net income divided by the total assets. Leverage represents the firms' long-term solvency and is defined by the total debt divided by total asset. Quick ratio measures the firms' short-term liquidity and can be estimated as the sum of total amount of cash and cash equivalents, marketable securities and accounts receivable divided by current liabilities. To estimate the performance measure specific to the insurance industry, we use the expense ratio measure. Expense ratio is used to measure firms insured losses compared to received premiums. Using the National Association of Insurance Commissioners (NAIC) insurance term glossary, expense ratio is defined by the percentage of premium income used to attain and service policies, derived by subtracting related expenses from incurred losses and dividing by written premiums. Table 1 provides a summary statistics of the financial performance features of the 132 firms in our sample period.

Table 1: Summary Statistics of Financial Performance Features

Variable	Mean	Standard deviation	Min	Max
Leverage	0.550	1.048	0.000	9.749
ROA	0.022	0.038	-0.356	0.178
Quick ratio	0.842	0.923	0.020	9.051
Expense ratio	1.603	3.998	-1.588	45.042
Size	8.820	2.309	2.531	13.713

The *People* category in the S&P Capital IQ database provides a source of governance characteristic data under two sub-categories, *Board Member* and *Professional*. The Board Member category includes details on the name, title, role and background of each board member of the individual firms. The Professional category records the name, title and background of each top executives of the firm. With these two sub-categories, we are able to get the chair, director and top executives such as CEO, CFO in each firm to create a combination of board and top executive data to evaluate the governance characteristics of each firm.

4 Result

In this section, we present our result for the assessments of insurance firms' climate change response, governance and financial characteristics. The result of the two-step classification of firms' climate change response is presented according to their climate risk exposure as well as the adaptative level of climate risk exposure. Clustering results based on firms' financial characteristic and governance characteristics assessment described as a network according to the common board members and top executives are also presented in this section. Lastly, the use of a multiplex network clustering method to sequentially analyze firms' clustering pattern and attribute insurance firms' climate change characteristic to their financial, governance and industry characteristics is presented.

4.1 Climate Change Characteristics

We begin our assessment of climate change characteristics by showing the result of classifying the final total of 122 firms according to their risk exposure and adaptation levels, by implementing the two-step classification method discussed in section 2.3.1. Firms are initially separated into 4 segments according to their acute and chronic risk performance and further partitioned based on the adaptative level of the firms according to the main segment's dominant climate risk feature.

4.1.1 Climate Change Risk and Adaptive Level Splitting

Figure 7 shows the general classification of our sample of 122 firms based on their climate change acute and chronic risk features. Splitting by mean of the mean of climate change chronic features (blue line) and mean of acute features (red line), we obtain four segments: 'high acute & high chronic(HAHC),' 'high acute & low chronic (HALC),' 'low acute & high chronic (LAHC)' and 'low acute & low chronic (LALC)'. A distribution of the total number of firms and their industry within each climate change risk segment is presented in Table 2. There are 51 firms in LALC, 12 firms in LAHC, 13 firms in HALC and 46 firms in HAHC.

A distribution of the firms in each climate change risk segment by their industry sector is shown in Table 2. We find most of the casualty insurance firms (40) to have a high exposure to high acute and high chronic risk. This high exposure is due to the nature of the business within the sector which entails property and casualty insurance products. These products are more sensitive to climate change risks, especially acute risk. The occurrence of disasters such as earthquake, flood and storm increase their exposure and insured loss. We also observe a uniform distribution of surety insurance firms across the LALC, HALC and HAHC segments, with only 1 surety firm belonging to HALC segment. This distribution may be due to the role surety firms play as intermediate insurers, thus exposing them to other business risks. Sectors such as Acchealth, Hosmed and Life, focus on personal health or medical insurance and as such have a low acute and low chronic risk exposure as represented in the LALC segment.

After separating the firms into four main segments, we further split firms in each segment according to their adaptative level of the dominant climate change risk. To identify the dominant climate change impact and response in each segment, we focus on the HAHC, HALC and LAHC firms as shown in Figure 8. From the HAHC segments, we find that both acute (Figure 8a) and chronic firms (Figure 8b) have high responses to climate change risk. Most of the response points for acute (black points) and chronic (green points) overlap with the acute climate risk points (blue) and chronic climate risk points (brown) respectively, for these two graphs. Furthermore, the pecuniary impact of both acute and chronic risk significantly follow the related climate risk. Since the non-pecuniary impacts are low in both plots, our further splitting relies on acute and chronic pecuniary impact and their response features.

From Figure 8c, HALC firms present similar performance with HAHC firms (Figures 8a and 8b) when comparing pecuniary and non-pecuniary impact as well as response, thus we choose acute pecuniary impact and acute response features to further split the firms. In Figure 8d, pecuniary

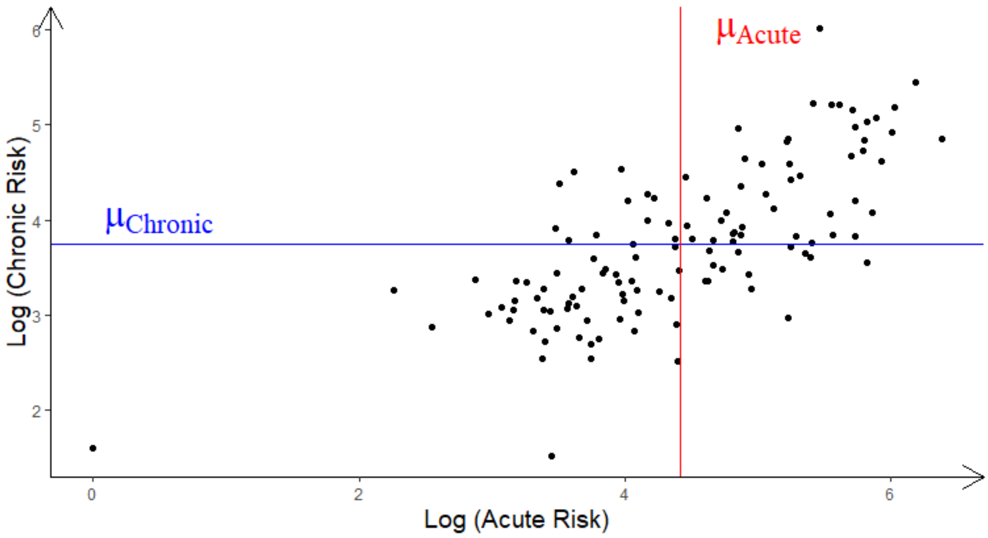
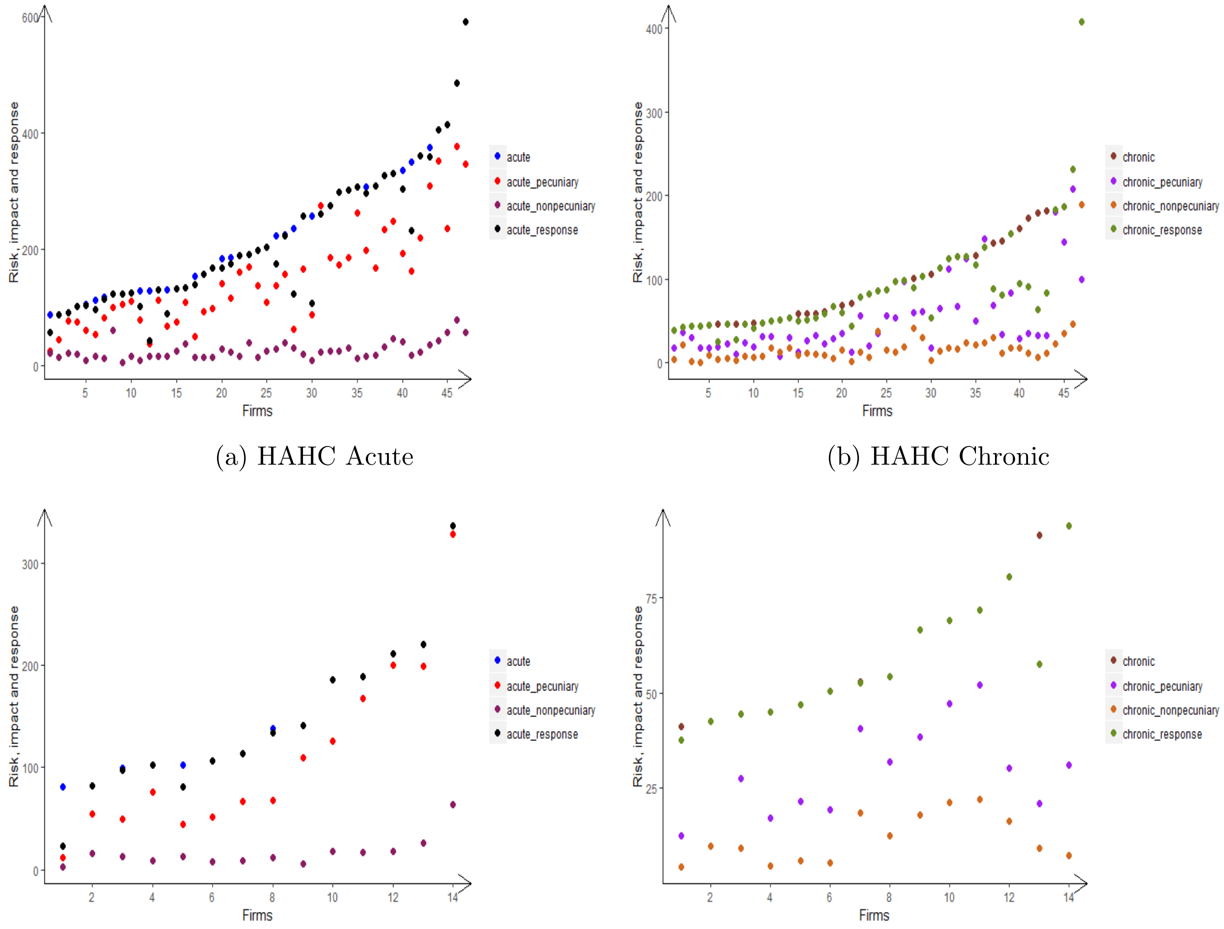


Figure 7: Climate Change Risk Splitting

Table 2: Distribution of Firms and Industry by Climate Change Risk

	Industry	Number of firms
LALC (51)	Acchealth	2
	Agents	9
	Casualty	13
	Hosmed	6
	Life	14
	Surety	4
	Title	3
LAHC (12)	Acchealth	1
	Agents	1
	Casualty	1
	Life	6
	Surety	3
HALC (13)	Agents	1
	Casualty	10
	Surety	1
	Hosmed	1
HAHC (46)	Agents	1
	Casualty	40
	Surety	3
	Life	2



(a) HAHC Acute (b) HAHC Chronic

(c) HALC (d) LAHC

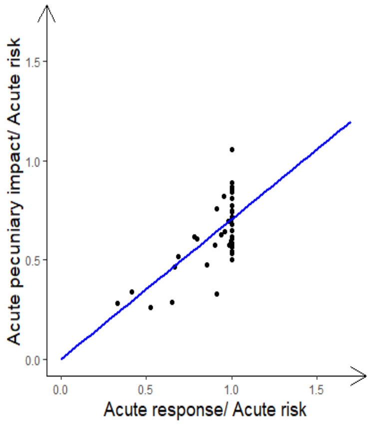
Figure 8: Further Classification of HAHC, HALC and LAHC Segments

impact shows no uniform trend making it not a good choice to set as the standard value for further classification. However, the non-pecuniary impact presents a combination of increasing and decreasing tendency with the increasing of chronic risk. The unusual trend makes chronic non-pecuniary a good measure for our further classification.

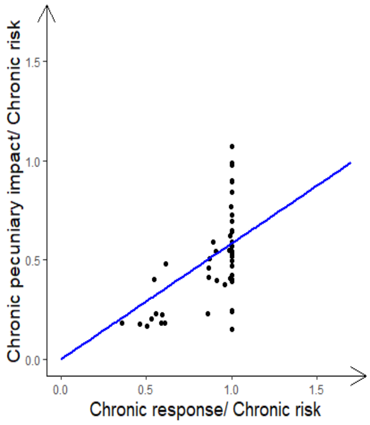
Thus, firms in the HAHC groups are further split by their acute pecuniary impact and acute response, and their chronic pecuniary impact and chronic response. Acute pecuniary impact and acute response are set as the adaptative splitting measures for HALC firms and chronic non-pecuniary and chronic response for LAHC firms.

4.1.2 Climate Change Characteristic Assessment

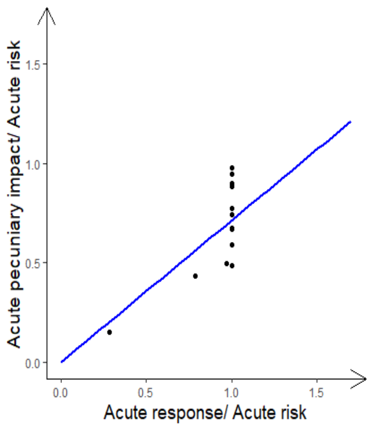
From the further classification of firms in Section 4.1.1 above, we run a regression analysis of the dominant climate risk impact on the response. The blue lines in Figures 9a, 9b, 9c and 9d represent the regression lines. The 122 firms are finally classified according to dominant climate change risk, related impact and respond.



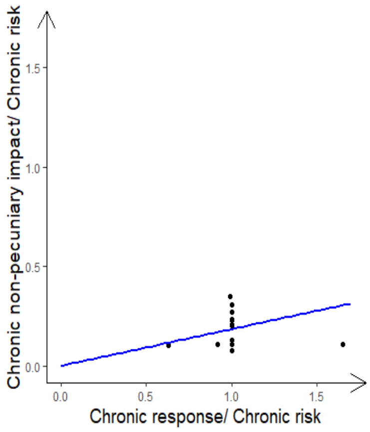
(a) Acute Pecuniary (HAHC)



(b) Chronic Pecuniary (HAHC)



(c) Acute Pecuniary (HALC)



(d) Chronic Non-Pecuniary (HAHC)

Figure 9: Further Classification in HAHC, HALC and LAHC Segments

The distribution of firms in each final segment is presented in Table 3. Casualty firms show a low climate change adaptive level as indicated by a large proportion of casualty firms within the BABC under the HAHC group. we find life insurance firms to have a high adaptation to chronic risk (LAHC - GC group). The business of life insurances focuses on personal living issues and the impact of chronic risk may include related diseases and the unavailability of living resources such as water and food, which are all life-related risks. Thus, more chronic risks are detected and prepared for by life insurers. On the contrary, surety firms adapt passively for chronic risk as they have a large proportion in GABC under the HAHC group.

4.2 Governance Characteristics

As discussed in Section 2.3.3, firms are also grouped according to their governance characteristics. The connection between the firms' board members and top executives can be seen in Figure 10, representing 14 groups formed in the governance network. The total number of firms with connections with at least one firm is 51 out of all 122 companies. The 51 firms consists of 15 LALC

Table 3: Further Classification in HAHC, HALC and LAHC Segments

Main	Sub	Industry	Number of firms
LAHC (14)	GC (8)	Acchealth	1
		Agents	1
		Casualty	1
		Life	4
		Surety	1
	BC (6)	Casualty	1
		Life	3
		Surety	2
HALC (14)	GA (6)	Casualty	5
		Hosmed	1
	BA (8)	Casualty	6
		Agents	1
		Life	1
HAHC (47)	GAGC (13)	Casualty	10
		Life	1
		Surety	2
	GABC (10)	Casualty	5
		Surety	5
	BAGC (6)	Casualty	5
		Surety	1
	BABC (18)	Casualty	15
		Surety	1
		Life	1
		Agents	1
LALC (47)	BABC (51)	Acchealth	2
		Agents	9
		Casualty	13
		Hosmed	6
		Life	14
		Surety	4
		Title	3

firms, 5 HALC firms, 7 LAHC firms and 14 HAHC firms. Firms in each group according to their governance characteristic is presented in Table 4.

The governance characteristics classification of firms consists of 15 groups. 14 groups are composed by at least 2 firms and 1 groups with 71 firms are consisted by single firms that with no connection with others in the governance level. Among 14 groups with firms' inner connections, group 3 is the biggest that contains 12 firms which evenly composed by firms in 7 casualty, 3 agents, 1 surety and 1 life industry sector. Group 7, which is the second biggest group contains 9 firms that is consisted by 6 casualty and 3 life firms. Group 6 contains 4 firms which are 2 surety and 2 life firms. The rest of the groups are all consisted by 2 or 3 firms for each. The result above indicates that Casualty,Life and Surety firms have with more governance connectivity with other firms when comparing with other industries.

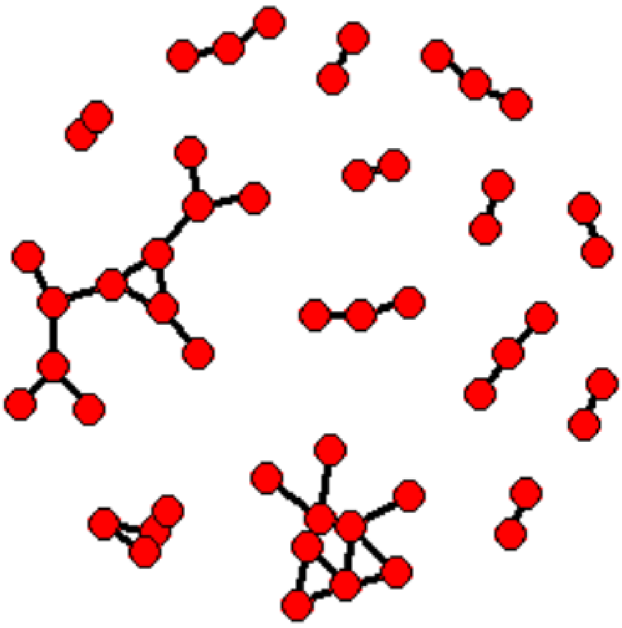


Figure 10: Governance Characteristic Network

4.3 Financial Characteristics

To assess the financial performance characteristics of firms, we first cluster our firms as discussed in Section 2.3.2. By ordering financial features according to the variance and correlation between the features, the cumulative cluster order is set as 'Leverage', 'ROA', 'Quick Ratio', 'Expense Ratio' and 'Size'. For instance, among the five variables, leverage had the highest variance and as such was the first feature to be added. The second added feature is ROA, with the second highest variance and lower correlation with leverage. Quick ratio is added as the third financial feature since it presents the third highest variance and relatively low correlation with both leverage and ROA features. The expense ratio and size are correspondingly added as the fourth and fifth features. The Table 5 below presents the Silhouette coefficient of clustering of 2 to 6 clusters according to the cumulative number of financial features.

From Table 5, size is dropped first due to the relatively low Silhouette score across the clusters. Using the highest silhouette score based on the combination of the the remaining variables, that is, leverage, ROA, quick ratio and expense ratio in a K-means clustering analysis, Cluster 5 is selected with a silhouette score of 0.455.

4.3.1 Financial Characteristics Assessment

From the 5 clusters, we label each cluster according to the total performance of their long-term solvency, profitability, short-term liquidity and industry operational cost ratio. Table 6 present the

Table 4: Governance Characteristic Clustering

Governance	Industry	Firms
1 (2)	Casualty	1
	Life	1
2 (3)	Casualty	3
3 (12)	Casualty	7
	Surety	1
	Life	1
	Agents	3
4 (3)	Casualty	1
	Surety	1
	Life	1
5 (2)	Casualty	1
	Life	1
6 (4)	Surety	2
	Life	2
7 (9)	Casualty	6
	Life	3
8 (2)	Casualty	1
	Surety	1
9 (2)	Hosmed	1
	Agents	1
10 (2)	Casualty	2
11 (2)	Acchealth	1
	Life	1
12 (3)	Surety	1
	Life	2
13 (2)	Casualty	1
	Life	1
14 (3)	Acchealth	1
	Casualty	2
None (71)	Acchealth	1
	Casualty	39
	Surety	5
	Title	3
	Life	8
	Hosmed	6
	Agents	9

mean of the financial features for each of 5 clusters.

We label Cluster 2 as the 'Best' cluster given it has the highest mean of quick ratio, the lowest leverage, the third largest ROA and the second least expense ratio. Cluster 4 presents the second-best financial performance ratios with the highest ROA, the lowest expense ratio and the third highest quick ratio. We label Cluster 4 as a 'Good' cluster. The 'Fair' cluster is set as Cluster 1 with a median of the financial features from all the clusters. Cluster 5 is labeled the 'Bad' cluster

Table 5: Silhouette Coefficient for Clustering

Cluster	+Leverage	+ROA	+Quick ratio	+Expense ratio	+Size
2	0.887	0.731	0.445	0.403	0.263
3	0.849	0.580	0.482	0.410	0.310
4	0.675	0.584	0.501	0.439	0.300
5	0.587	0.358	0.363	0.455	0.248
6	0.584	0.384	0.371	0.421	0.276

because it presents the highest leverage ratio, the second lowest ROA and the third highest of expense ratio. Although Cluster 5 presents the second highest quick ratio, it is better than Cluster 3, with the highest expense ratio and the lowest ROA and quick ratio. Consequently, Cluster 3 is labeled as 'Worst'. Table 2 shows a distribution of firms in each of the 5 financial characteristic clusters.

Table 6: Labeling of Financial Clusters

Cluster	Leverage	ROA	Quick ratio	Expense ratio	Label
1	0.630	0.589	0.732	1.029	Fair
2	0.441	0.428	4.005	0.729	Best
3	0.560	0.134	0.570	6.746	Worst
4	1.272	3.273	1.283	0.410	Good
5	9.028	0.175	1.327	0.819	Bad

According to Table 7, most of the casualty firms present fair financial performance since most of these firms are belong to 'Fair' cluster. Acchealth and hosmed firms present relatively good financial performance since at least nearly or over half of firms in these two industry are belong to 'Good' and 'Best' cluster. Agents firms present the best performance since almost all of the firms are in the 'Best' cluster. However, life insurance generally presents a low financial performance since all of these firms are in 'Bad' even 'Worst' clusters.

4.4 Multiplex Network Clustering Analysis

After assessing the firms' climate change, financial and governance characteristics, we combining the 3 layers into a multiplex network. Firms in different groups, clusters and industry are transformed into clusters. Thus, a sequential clustering identification can be conducted according to the hierarchical relationships of the multiplex network. Table 8, 9 and 10 explain the structure of the multiplex network for HAHC, HALC, LAHC and LALC firms.

From Table 8, 2 casualty firms, Arch Capital Group Ltd. and AXIS Capital Holdings Ltd., have HAHC climate risk with a BABC (Bad Acute Bad Chronic) response level. These firms are connected by the same 'Fair' financial cluster and governance cluster. Similarly, CNA Financial Corp. and Loews Corp. are two casualty firms also connected by all three characteristics with a 'Fair' financial cluster. Furthermore, A casualty firm HCI Group Inc. and an agent firm Verisk Analytics Inc. are also connected by all three characteristics with a 'Good' Financial cluster.

Table 7: Firm Characteristic Clustering

Cluster	Industry	Firms
1 (90)	Acchealth	2
	Casualty	56
	Surety	6
	Title	2
	Life	18
	Hosmed	2
	Agents	4
2 (6)	Acchealth	1
	Casualty	4
	Agents	1
3 (2)	Life	2
4 (20)	Casualty	3
	Surety	3
	Title	1
	Hosmed	5
	Agents	8
5 (4)	Casualty	1
	Surety	2
	Life	1

Moreover, all firms with HAHC climate risk and BAGC (Bad Acute Good Chronic) climate response are in ‘Fair’ financial cluster. In this ‘Fair’ cluster, a casualty firm which is American International Group Inc. and a surety group which is Argo Group International Holdings Ltd. are connected by all three characteristics.

For the 10 firms in HAHC and GABC (Good Acute Bad Chronic) climate change cluster, 8 belong to the ‘Fair’ cluster and 2 belong to the fourth cluster which represents ‘Good’ financial performance. The last climate cluster in this table are firms with HAHC and GAGC (Good Acute Good Chronic) climate change characteristics. Most of the firms in this cluster have a ‘Fair’ financial characteristic with only one firm in with a ‘Best’ financial characteristic. Firms with HAHC climate risk exposures mostly perform fair in their finances. However, for the worst climate response cluster, which is HAHC & BABC, some firms are related in the best or good financial performance clusters.

Table 9 presents the multiplex clustered network for HALC and LAHC climate risk exposure. For firms with high acute low chronic risk with bad acute adaptation, a casualty firm which is National General Holdings Corp. and a life firm which is American National Insurance Company are connected by three characteristics with a ’Fair’ financial performance. There are also 1 and 2 firms in this high climate risk low preparedness level cluster that can be found in the best and good financial characteristic clusters. Firms with good acute adapting level for the HALC exposure all belong to the fair financial cluster.

When looking at firms in the LAHC climate risk clusters, 2 casualty firms which are AmTrust Financial Services Inc. and Maiden Holdings Ltd. as well as a life firm which is Lincoln National Corp. can be found in the same governance and fair financial clusters. A casualty firm in the LAHC

Table 8: Multiplex Network Clustering for HAHC Firms

Climate Change	Financial	Governance	Industry	Firms
HAHC_BABC (18)	1 (14)	3 (2)	Casualty	2
		7 (1)	Casualty	1
		8 (1)	Casualty	1
		10 (2)	Casualty	2
		None (8)	Casualty Surety Agents	6 1 1
	2 (2)	None (2)	Casualty	2
	4 (2)	3 (2)	Casualty Agents	1 1
HAHC_BAGC (6)	1 (6)	3 (2)	Casualty Surety	1 1
		4 (1)	Casualty	1
		14 (1)	Casualty	1
		None (2)	Casualty	2
HAHC_GABC (10)	1 (8)	5 (1)	Casualty	1
		7 (1)	Casualty	1
		13 (1)	Casualty	1
		14 (1)	Casualty	1
		None (4)	Casualty Surety	3 1
	4 (2)	3 (1) None (1)	Casualty Casualty	1 1
HAHC_GAGC (13)	1 (12)	1 (1)	Casualty	1
		4 (1)	Surety	1
		6 (1)	Life	1
		None (9)	Casualty	9
	2 (1)	None (1)	Casualty	1

& BC cluster can be found in 'Worst' cluster of financial characteristics. The last climate cluster in this table is the LAHC firms with good preparedness for chronic risk. Most of these firms have on average a good financial performance with 1 casualty firm showing a worst financial performance.

Table 10 shows the 3-layer network for LALC firms. Most of these firms have a fair financial performance and 4 of them even belong to 'Bad' and 'Worst' financial clusters. Approximate 28% firms also perform well for their financial characteristic. However, these 47 firms are less attractive for further analysis since their climate risk exposure is extremely low according to their 10-k textual data.

Examining Table 8 and 9 together, we find out that for firms with low response to high climate

Table 9: Multiplex Network Clustering for HALC & LAHC Firms

Climate Change	Financial	Governance	Industry	Firms
HALC_BA	1 (5)	2 (1)	Casualty	1
		3 (1)	Casualty	1
		7 (2)	Casualty Life	1 1
		None (1)	Casualty	1
	2 (1)	None (1)	Casualty	1
	4 (1)	3 (1)	Agents	1
		None (1)	Agents	1
HALC_GA	1 (6)	None (6)	Casualty Hosmed	5 1
LAHC_BC	1 (6)	4 (1)	Life	1
		7 (2)	Casualty Life	2 1
		None (1)	Surety	1
	5 (1)	8 (1)	Surety	1
LAHC_GC	1 (5)	5 (1)	Life	1
		12 (1)	Life	1
		None (3)	Casualty Life Agents	1 1 1
	2 (1)	14 (1)	Acchealth	1
	4 (1)	None (1)	Surety	1
	5 (1)	6 (1)	Life	1

Table 10: Multiplex Network Clustering for LALC Firms

Climate Change	Financial	Governance	Industry	Firms
LALC	1 (29)	1 (1)	Life	1
		2 (1)	Casualty	1
		3 (3)	Casualty	1
			Life	1
			Agents	1
		7 (2)	Casualty	1
			Life	1
		9 (1)	Hosmed	1
		11 (2)	Acchealth	1
			Life	1
		13 (1)	Life	1
		None (18)	Acchealth	1
			Casualty	7
			Surety	1
			Title	2
			Life	6
			Agents	1
	2 (1)	None (1)	Agents	1
	3 (2)	12 (1)	Life	1
		None (1)	Life	1
	4 (13)	6 (1)	Surety	1
		9 (1)	Agents	1
		12 (1)	Surety	1
		None (10)	Title	1
			Hosmed	5
			Agents	4
	5 (2)	2 (1)	Casualty	1
		6 (1)	Surety	1

change risk exposure, there are more overlapping clusters especially for a fair financial performance, governance characteristics and within industry sectors. On the contrary, there are no overlapping connections for the financial, governance and industry sector clusters for good climate change response firms. Firms with bad climate change responses tend to be highly connected by different firm characteristics including low financial performance. While there is almost no network connections for firms with a good climate change adaptation.

5 Conclusion

In this paper, we assess U.S. public insurance firms' climate change response using a sample of 10-K regulatory filings and attribute their response to their financial and governance characteristics. Using a climate change dictionary consisting of climate change risk, impact and response sub-dictionaries as the reference of the feature extraction process, we define climate change risk exposure and response features. To enhance the accuracy of the extraction, we conduct a nested structure extraction to capture firms' climate change response. The assessment of climate change characteristic is based on the climate risk exposure and the adaptative level of insurance firms. Governance characteristic is assessed by the connection between board members and top executives. Financial characteristics are then be assessed according to the liquidity, profitability, leverage and industry specific operational loss. When combining all of three layers' network into a multiplex layer network, a sequential clustering analysis is conducted to attribute firms' climate change response characteristic to their financial and governance characteristics.

Analysis at the industry sector also shows that most casualty and surety insurance firms are threatened by high climate change risk, with a high exposure to chronic risk for surety firms. The governance characteristic assessment results indicate casualty, surety and life insurance firms are active in governance network level. However, the assessment results of financial characteristics imply the life insurers' low financial performance and the high financial performance of agent firms. Our result of multiple network clustering analysis indicates insurance firms with bad response for high climate change risk exposure tend to have fair financial performance ratios with a high connection in governance characteristics. While firms that actively react to climate change present low further connections on their other characteristics. Identification of this relationship will help advice the favorable factors that enhance the propensity of insurance firms to develop a climate risk strategy.

For further research direction, more data needs to be accessed from governance data source such as Boardex database to create a more complete network in firms' governance prospect. Adding different characteristics such as geographical connection can also be an improvement for our current attribution process. Moreover, graph analysis may be further implemented to attribute firms' climate change characteristics. With the enlarging of the governance data as well as more precise analysis approaches, we will be able to more effectively attribute firms' climate change responses.

References

Bloomberg, M., Pavarina, D., Pitkethly, G., Thimann, C., and Sim, Y. (2017). Final report: Recommendations of the task force on climate-related financial disclosures.

Changnon, S. A. (2003). Shifting economic impacts from weather extremes in the united states: A result of societal changes, not global warming. *Natural Hazards*, 29(2):273–290.

Creamer, G. G., Ren, Y., Sakamoto, Y., and Nickerson, J. V. (2016). A textual analysis algorithm for the equity market: The european case. *The Journal of Investing*, 25(3):105–116.

Elum, Z. A. and Simonyan, J. B. (2016). Analysis of nigerian insurers' perceptions of climate change. *South African Journal of Economic and Management Sciences*, 19(4):549–561.

Engle III, R. F., Giglio, S., Kelly, B. T., Lee, H., and Stroebel, J. (2019). Hedging climate change news. Technical report, National Bureau of Economic Research.

Fecamp, S., Mikael, J., and Warin, X. (2019). Risk management with machine-learning-based algorithms. *arXiv preprint arXiv:1902.05287*.

Field, C. B., Barros, V., Stocker, T. F., and Dahe, Q. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.

Groth, S. S. and Muntermann, J. (2011). An intraday market risk management approach based on textual analysis. *Decision Support Systems*, 50(4):680–691.

Gupta, A. and Owusu, A. (2019). Identifying the risk culture of banks using machine learning. *Available at SSRN 3441861*.

Hecht, S. B. (2007). Climate change and the transformation of risk: Insurance matters. *UCLA L. Rev.*, 55:1559.

Keskitalo, E. C. H., Vulturius, G., and Scholten, P. (2014). Adaptation to climate change in the insurance sector: examples from the uk, germany and the netherlands. *Natural Hazards*, 71(1):315–334.

Kousky, C. and Cooke, R. M. (2009). Climate change and risk management: challenges for insurance, adaptation, and loss estimation.

Li, F. (2010). The information content of forward-looking statements in corporate filings—a naïve bayesian machine learning approach. *Journal of Accounting Research*, 48(5):1049–1102.

MacQueen, J. et al. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1(14), pages 281–297. Oakland, CA, USA.

Maynard, T. (2008). Climate change: Impacts on insurers and how they can help with adaptation and mitigation. *The Geneva papers on risk and insurance-Issues and practice*, 33(1):140–146.

Mills, E. (2003). Climate change, insurance and the buildings sector: technological synergisms between adaptation and mitigation. *Building Research & Information*, 31(3-4):257–277.

Mills, E. (2005). Insurance in a climate of change. *Science*, 309(5737):1040–1044.

Mills, E. (2012). The greening of insurance. *Science*, 338(6113):1424–1425.

Milly, P. C. D., Wetherald, R. T., Dunne, K., and Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature*, 415(6871):514.

Ntim, C. G., Lindop, S., and Thomas, D. A. (2013). Corporate governance and risk reporting in south africa: A study of corporate risk disclosures in the pre-and post-2007/2008 global financial crisis periods. *International Review of Financial Analysis*, 30:363–383.

Pollard, J. S., Oldfield, J., Randalls, S., and Thornes, J. E. (2008). Firm finances, weather derivatives and geography. *Geoforum*, 39(2):616–624.

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, 20:53–65.

Shivdasani, A. and Yermack, D. (1999). Ceo involvement in the selection of new board members: An empirical analysis. *The journal of finance*, 54(5):1829–1853.

Stechemesser, K., Endrikat, J., Grasshoff, N., and Guenther, E. (2015). Insurance companies' responses to climate change: Adaptation, dynamic capabilities and competitive advantage. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 40(4):557–584.

Thomas, A. and Leichenko, R. (2011). Adaptation through insurance: lessons from the nfip. *International Journal of Climate Change Strategies and Management*, 3(3):250–263.

Tornyeva, K. and Wereko, T. (2012). Soft governance and firm performance: a study of ghanaian insurance firms. *European Journal of Business and Management*, 4(13):6–94.

Appendix A Source of Climate Change Dictionary

To construct an exclusive and scientific climate change dictionary we collect 33 climate change white papers and climate reports from sources include Intergovernmental Panel on Climate Change (IPCC), U.S. Environmental Protection Agency (EPA), International Monetary Fund (IMF), U.S. Global Change Research Program, Task Force on Climate-Related Financial Disclosures (TCFD), United Nations Environmental Programme (UNEP) and Network for Green the Financial System (NGFS). Table A1 presents the title, providing institution and published year of the 33 climate change white papers and reports.

Furthermore, 59 climate glossaries such as EPA, WHO and IPCC according to Engle et al. (2019) (Engle III et al., 2019) are also added to information source to enlarge our climate change repository for dictionary construction. The following 24 climate change glossaries out of the 59 provide a source of the words and phrases that make up the climate change dictionary:
U.S. Environmental Protection Agency (EPA), BBC, United Nations(UN), Center for Climate and Energy Solutions Glossary of Key Terms, Intergovernmental Panel on Climate Change (IPCC), World Health Organization (WHO), European Climate Adaptation Platform, Wikipedia, Guardian, New York Times, Natural Climate Change, UN Climate Change Conference, UK Climate Impacts Programme (UKCIP), Climate Policy Information Hub, Explaining Climate Change, Four Degrees Preparation, The European Initiative for Upscaling Energy Efficiency in the Music Event Industry (EE MUSIC), Regional Education and Information Centre (REIC), Ecology, Climate Reality Project, National Geographic, Agricultural Marketing Resource Center (AgMRC), Global Greenhouse Warming, Conservation in a Changing Climate.

Table A1: List of Climate Change White Papers and Reports

Source	Title	Year
Intergovernmental Panel on Climate Change (IPCC)	IPCC Synthesis Report	1990, 1995, 2001,2007, 2014
	IPCC Special Report: The regional impacts of climate change : an assessment of vulnerability	1997
	IPCC IPCC Special Report : Aviation and the Global Atmosphere	1999
	IPCC Special Report : Methodological and Technological Issues in Technology Transfer	2000
	IPCC Special Report : Safeguarding the Ozone Layer and the Global Climate System: Issues Related to Hydrofluorocarbons and Perfluorocarbons	2005
	IPCC Special Report : Carbon Dioxide Capture and Storage	2005
	IPCC Special Report : Renewable Energy Sources and Climate Change Mitigation	2011
	IPCC Special Report : Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation	2012
	Climate Change 2013: The Physical Science Basis	2013
	AR5 Climate Change 2014: Impacts, Adaptation, and Vulnerability	2014
	AR5 Climate Change 2014: Mitigation of Climate Change	2014
	Special Reports: Global Warming of 1.5 °C	2018
Task Force on Climate-Related Financial Disclosures (TCFD)	Draft Technical Supplement: The Use of Scenario Analysis in Disclosure of Climate-related Risks and Opportunities	2016
	Technical Supplement: The Use of Scenario Analysis in Disclosure of Climate-related Risks and Opportunities	2017
	Final Report: Recommendations of the Task Force on Climate-related Financial Disclosures	2017
	2018 Status Report	2018
	2019 Status Report	2019
Network for Green the Financial System (NGFS)	A Call for Action Climate Change as a Source of Financial Risk	2019
U.S. Federal Government	New Green Deal	2019
U.S. Environmental Protection Agency (EPA)	Climate Change Indicators in the United States (4th Edition)	2016
	Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2014	2016
	EPA's Report on the Environment (ROE)	
International Monetary Fund (IMF)	The Effects of Weather Shocks on Economic Activity	2017
U.S. Global Change Research Program	Our change planet : The U.S. Global Change Research Program for Fiscal Year 2017	2017
	Climate Science Special Report (4th National Climate Assessment, Volume I)	
United Nations Environmental Programme (UNEP)	UN Environment 2016 Annual Report: Empowering People to Protect the Planet	2017
	Annual Report 2017	2018
	Share the Road Programme - Annual Report 2017: Investing in People who Walk and Cycle	2018